Offline Components:
Collaborative Filtering in Cold-start Situations

Problem Definition

Algorithm selects Item j with item features $\boldsymbol{x}_j$

(keywords, content categories, ...)

User i visits with user features $\boldsymbol{x}_i$

(demographics, browse history, search history, …)

(i, j) : response y_{ij}

(rating or click/no-click)

Predict the unobserved entries based on features and the observed entries

Model Choices

- Feature-based (or content-based) approach
  - Use features to predict response (regression, Bayes Net, mixture models, …)
  - Bottleneck: need predictive features
    - Does not capture signals at granular levels
- Collaborative filtering (CF aka Memory based)
  - Make recommendation based on past user-item interaction
    - User-user, item-item, matrix factorization, …
    - See [Adomavicius & Tuzhilin, TKDE, 2005], [Konstan, SIGMOD'08 Tutorial], etc.
  - Better performance for old users and old items
  - Does not naturally handle new users and new items (**cold-start**)

Collaborative Filtering (Memory based methods)

User-User Similarity

$$p_{a,j} = \overline{v}_a + \kappa \sum_{i=1}^{n} w(a,i)(v_{i,j} - \overline{v}_i)$$

Item-Item similarities, incorporating both

Estimating Similarities

- Pearson's correlation
- Optimization based (Koren et al)

How to Deal with the Cold-Start Problem

- Heuristic-based approaches
  – Linear combination of feature-based and CF models
    - Learn weights adaptively at user level
  – Filterbot
    - Add user features as psuedo users and do collaborative filtering
  - Hybrid approaches
    - Use content based to fill up entries, then use CF
- Model-based approaches
  – Mixed kernel learnt jointly
    - Popularity, features, user-user similarities, item-item similarities
  – Bayesian mixed-effects models
    - Given modeling assumptions are reasonable: state-of-the-art
- Drilldown
  – Matrix factorization
    - Superior than others on Netflix data [Koren, 2009], also on our Yahoo! data
  – Add feature-based regression to matrix factorization
  – Add topic discovery (from textual items) to matrix factorization

Per-user, per-item models via bilinear random-effects model

Matrix Factorization

Motivation

- Data measuring k-way interactions pervasive
  - Consider k = 2 for all our discussions
  - E.g. User-Movie, User-content, User-Publisher-Ads,….
- Classical Techniques
  - Approximate matrix through a singular value decomposition (SVD)
    - After adjusting for marginal effects (user pop, movie pop,..)
  - Does not work
    - Matrix highly incomplete, overfit very easily
  - Key issue
    - Putting constraints on the eigenvectors (factors) to avoid overfitting

Early work in the literature

- Tukey's 1-df model (1956)
  - Rank 1 approximation of small nearly complete matrix

- Criss-cross regression (Gabriel, 1978)
- Incomplete matrices: Psychometrics (1-factor model only; small data sets; 1960s)
- Modern day web datasets
  - Highly incomplete, large, noisy.

Factorization – Brief Overview

- Latent user factors: (α_i , $\mathbf{u_i}=(u_{i1},\ldots,u_{in})$)
- Latent movie factors: (β_j , $\mathbf{v_j}=(v_{j1},\ldots,v_{jn})$)

Interaction

$$E(y_{ij}) = \mu + \alpha_i + \beta_j + u_i' B v_j$$

- (Nn + Mm) parameters → will overfit for moderate values of n,m
- Key technical issue: → *Regularization*

Model: Different choices of factors

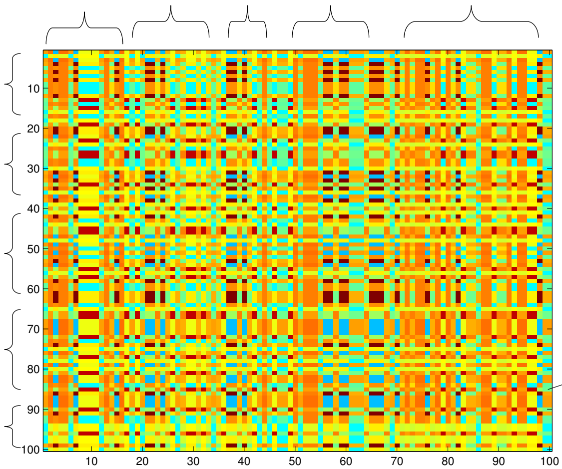
- Bi-Clustering
  - Hard, Soft

- Matrix Factorization
  - Factors in Euclidean space
  - Regularization

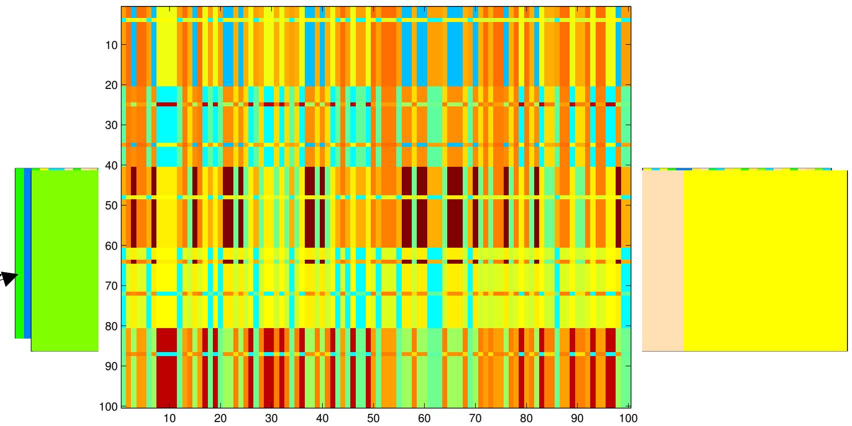
- Incorporating features
- Online updates

BICLUSTERING: Iterative row and column k-means

RAW DATA



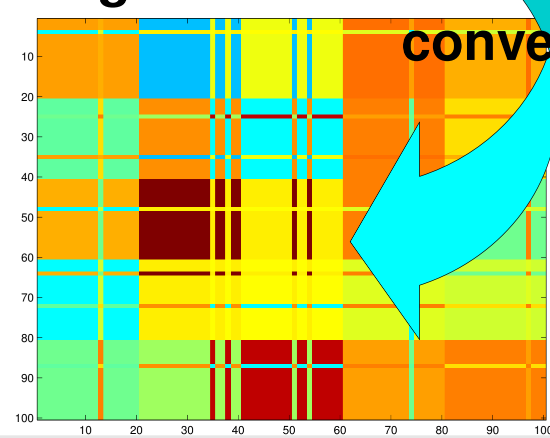
After ROW CLUSTERING

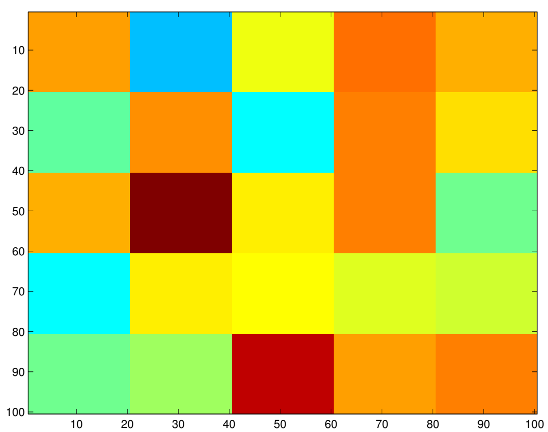


Smooth Rows using column clusters; reduce variance

After COLUMN Clustering

Iterate Until convergence





Bi-Clustering can be represented as factorization

- m user clusters, n item clusters

$$u_i, v_j: \text{ Cluster membership weights.}$$

$$\mathbf{1}' u_i = \mathbf{1}' v_j = 1$$

- *B*: bi-cluster means
- Hard-clustering
  - Each row(col) belongs to exactly one cluster
- Soft-clustering
  - Weighted assignment to several clusters

Factors in Euclidean space

- Latent user factors: $(\alpha_i\ ,\ \mathbf{u_i}=(u_{i1},\ldots,u_{ir}))$
- Latent movie factors: $(\beta_j\ ,\ \mathbf{v_j}=(v_{j1},\ldots,v_{jr}))$

Interaction

$$\alpha_i + \beta_j + u_i' v_j$$

- (N + M)(r+1) parameters → will overfit for moderate values of *r*

- Key technical issue: → *Regularization*
- Usual approach: → Gaussian ZeroMean prior

Existing Zero-Mean Factorization Model

Observation Equation

$$y_{ij} \sim N(m_{ij}, \sigma^2)$$

$$m_{ij} = x'_{ij}\boldsymbol{b} + \alpha_i + \beta_j + u'_i v_j$$

State Equation

$$\alpha_i \sim N(0, a_\alpha)$$

$$\beta_j \sim N(0, a_\beta)$$

$$u_i \sim MVN(\mathbf{0}, A_u)$$

$$v_j \sim MVN(\mathbf{0}, A_v)$$

Predict for new cell: $(x_{ij}^{new})'\hat{\boldsymbol{b}} + \hat{\alpha}_i + \hat{\beta}_j + \hat{u}'_i \hat{v}_j$

PROBLEM DEFINITION

- Models to predict ratings for *new* pairs
  - Warm-start: (user, movie) present in the training data
  - Cold-start: At least one of (user, movie) new

- Challenges
  - Highly incomplete (user, movie) matrix
  - Heavy tailed degree distributions for users/movies
    - Large fraction of ratings from small fraction of users/movies
  - Handling both warm-start and cold-start effectively

Possible approaches

- Large scale regression based on covariates
  - Does not provide good estimates for heavy users/movies
  - Large number of predictors to estimate interactions
- Collaborative filtering
  - Neighborhood based
  - Factorization (our approach)
  - Good for warm-start; cold-start dealt with separately
- Single model that handles cold-start and warm-start
  - Heavy users/movies → User/movie specific model
  - Light users/movies → fallback on regression model
  - **Smooth** fallback mechanism for good performance

Add Feature-based Regression into Matrix Factorization

RLFM: Regression-based Latent Factor Model

Regression-based Factorization Model (RLFM)

- Main idea: Flexible prior, predict factors through regressions
- Seamlessly handles cold-start and warm-start
- Modified state equation to incorporate covariates

RLFM: Model

- **Rating:** $y_{ij} \sim N(\mu_{ij}, \sigma^2)$ Gaussian Model

  user i gives item j

  $y_{ij} \sim Bernoulli(\mu_{ij})$ Logistic Model (for binary rating)

  $y_{ij} \sim Poisson(\mu_{ij} N_{ij})$ Poisson Model (for counts)

$$t(\mu_{ij}) = x_{ij}^t b + \alpha_i + \beta_j + u_i^t v_j$$

- **Bias of user *i*:** $\alpha_i = g_0^t x_i + \varepsilon_i^\alpha, \quad \varepsilon_i^\alpha \sim N(0, \sigma_\alpha^2)$
- **Popularity of item *j*:** $\beta_j = d_0^t x_j + \varepsilon_j^\beta, \quad \varepsilon_j^\beta \sim N(0, \sigma_\beta^2)$
- **Factors of user *i*:** $u_i = G x_i + \varepsilon_i^u, \quad \varepsilon_i^u \sim N(0, \sigma_u^2 I)$
- **Factors of item *j*:** $v_i = D x_j + \varepsilon_i^v, \quad \varepsilon_i^v \sim N(0, \sigma_v^2 I)$

Could use other classes of regression models

Advantages of RLFM

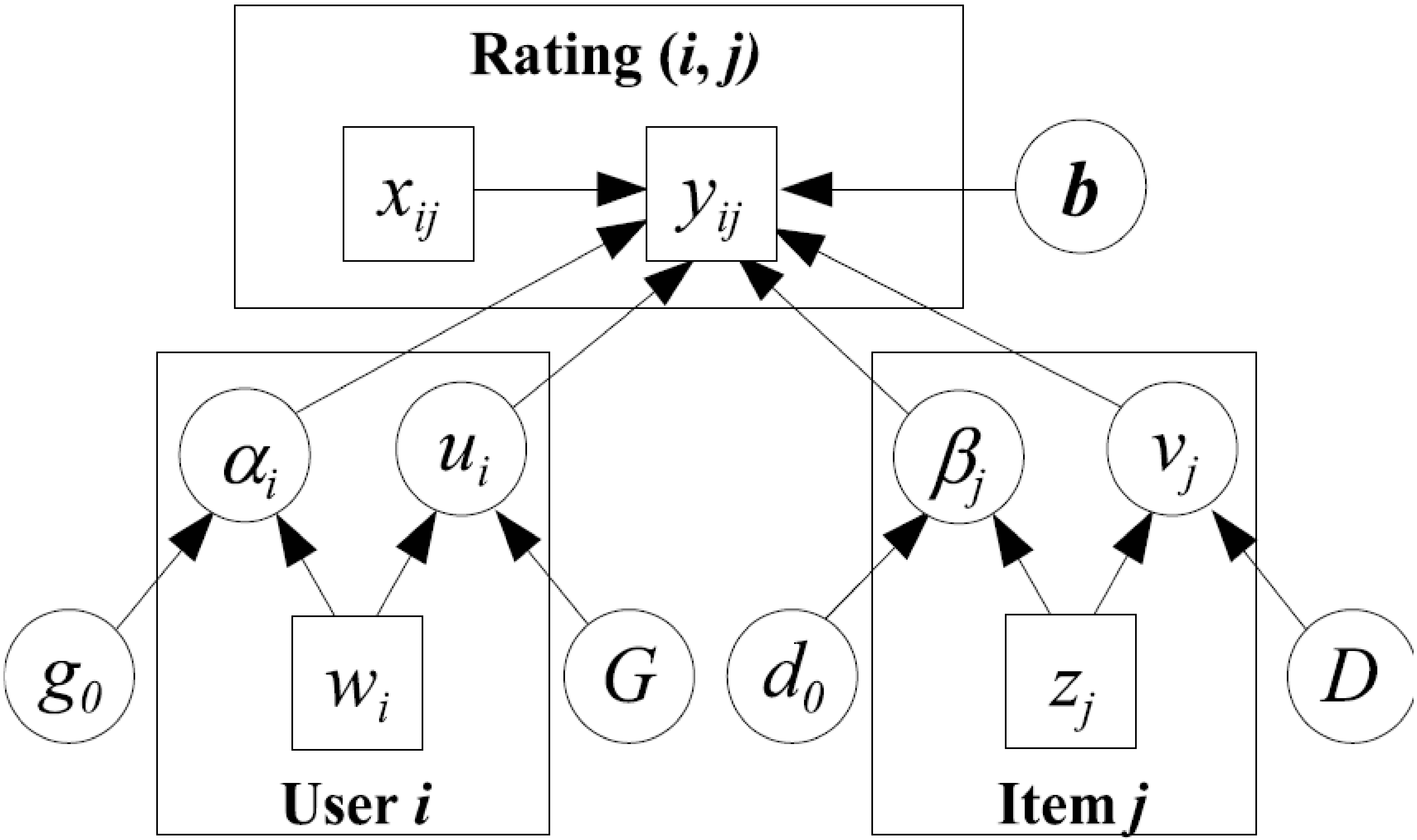
- Better regularization of factors
  - Covariates "shrink" towards a better centroid

- Cold-start: Fallback regression model (**FeatureOnly**)

$$y_{ij} \sim N(m_{ij}, \sigma^2)$$

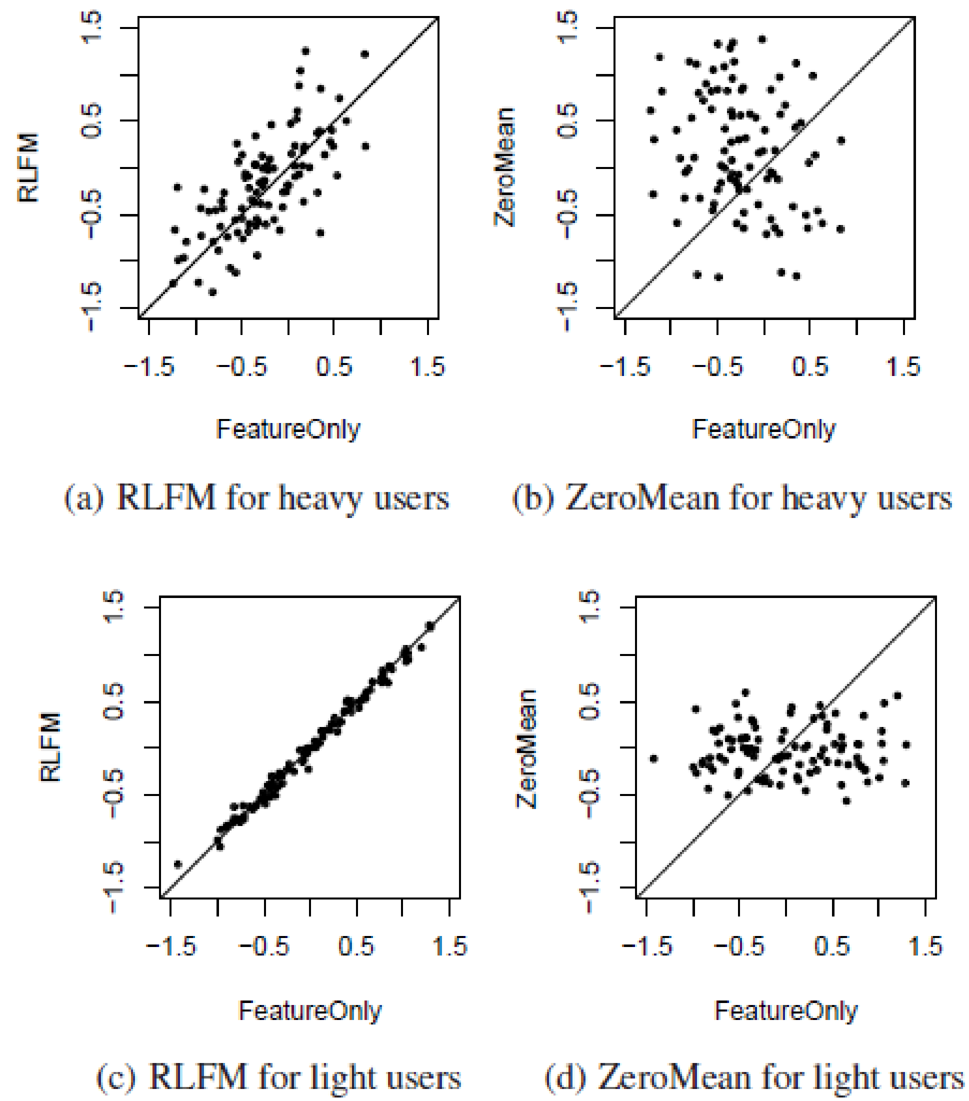
$$m_{ij} = x'_{ij}\mathbf{b} + g'_0 w_i + d'_0 z_j + w'_i G' D z_j$$

Graphical representation of the model



RLFM: Illustration of Shrinkage

Plot the first factor value for each user
(fitted using Yahoo! FP data)



(a) RLFM for heavy users

(b) ZeroMean for heavy users

(c) RLFM for light users

(d) ZeroMean for light users

Induced correlations among observations

Hierarchical random-effects model

Marginal distribution obtained by integrating out random effects

$$y_{ij} \sim N(m_{ij}, \sigma^2)$$

$$m_{ij} = x'_{ij}\boldsymbol{b} + \alpha_i + \beta_j + u'_i v_j$$

$$\alpha_i = g'_0 w_i + \epsilon_i^{\alpha}, \quad \epsilon_i^{\alpha} \sim N(0, a_{\alpha})$$

$$\beta_j = d'_0 z_j + \epsilon_j^{\beta}, \quad \epsilon_j^{\beta} \sim N(0, a_{\beta})$$

$$u_i = G w_i + \epsilon_i^{u}, \quad \epsilon_i^{u} \sim MVN(\mathbf{0}, A_u)$$

$$v_j = D z_j + \epsilon_j^{v}, \quad \epsilon_j^{v} \sim MVN(\mathbf{0}, A_v)$$

Closer look at induced marginal correlations

$$E(y_{ij}) = x_{ij}'\boldsymbol{b} + g_0'w_i + d_0'z_j + w_i'G'Dz_j$$

$$Var(y_{ij}) = \sigma^2 + a_\alpha + a_\beta + tr(A_uA_v) + z_j'D'A_uDz_j + w_i'G'A_vGw_i$$

$$cov(y_{ij}, y_{ij*}) = a_\alpha + z_j'D'A_uDz_{j*}$$

$$cov(y_{ij}, y_{i*j}) = a_\beta + w_i'G'A_vGw_{i*}$$

Overview: EM for our class of models

$$\boldsymbol{Y} : \text{ Data}$$

$$\boldsymbol{\Delta} : \text{ Latent variables}$$

$$\boldsymbol{\Theta} : \text{ hyper-parameters}$$

$$\text{Model: } p(\boldsymbol{Y}|\boldsymbol{\Delta}, \boldsymbol{\Theta})p(\boldsymbol{\Delta}|\boldsymbol{\Theta})$$

$$\text{Output needed: } \text{ Mode: } max_{\boldsymbol{\Theta}} p(\boldsymbol{\Theta}|\boldsymbol{Y})$$

$$p(\boldsymbol{\Delta}|\boldsymbol{Y}) \approx p(\boldsymbol{\Delta}|\boldsymbol{Y}, \hat{\boldsymbol{\Theta}})$$

The parameters for RLFM

- Latent parameters

$$\Delta = (\{\alpha_i\}, \{\beta_j\}, \{u_i\}, \{v_j\})$$

- Hyper-parameters

$$\Theta = (\mathbf{b}, \mathrm{G}, \mathrm{D}, \mathrm{A}_{\mathrm{u}} = \mathrm{a}_{\mathrm{u}}\mathrm{I}, \mathrm{A}_{\mathrm{v}} = \mathrm{a}_{\mathrm{v}}\mathrm{I})$$

Computing the mode

$$log(p(\mathbf{\Theta}|\boldsymbol{Y})) = log(p(\mathbf{\Theta}, \mathbf{\Delta}|\boldsymbol{Y})) - log(p(\mathbf{\Delta}|\mathbf{\Theta}, \boldsymbol{Y}))$$

$$log(p(\mathbf{\Theta}|\boldsymbol{Y})) = E_{old}(log(p(\mathbf{\Theta}, \mathbf{\Delta}|\boldsymbol{Y}))) - E_{old}(log(p(\mathbf{\Delta}|\mathbf{\Theta}, \boldsymbol{Y})))$$

$$E_{old}: \text{ Expectation w.r.t. } p(\mathbf{\Delta}|\mathbf{\Theta}_{old}, \boldsymbol{Y})$$

Second term: Maximized at $\mathbf{\Theta}_{old}$

Find new value of $\mathbf{\Theta}$ that increases first term

The EM algorithm

Initialize $\mathbf{\Theta}$

Iterate

$$\text{E-step} \quad : E_{old}(log(p(\mathbf{\Theta}, \mathbf{\Delta} | \boldsymbol{Y})))$$

$$\text{M-step} \quad : argmax_{\mathbf{\Theta}} E_{old}(log(p(\mathbf{\Theta}, \mathbf{\Delta} | \boldsymbol{Y})))$$

Computing the E-step

- Often hard to compute in closed form
- Stochastic EM (Markov Chain EM; MCEM)
  - Compute expectation by drawing samples from

$$p(\mathbf{\Delta}|\mathbf{\Theta}_{old}, \mathbf{Y})$$

  - Effective for multi-modal posteriors but more expensive
- Iterated Conditional Modes algorithm (ICM)
  - Faster but biased hyper-parameter estimates

$$\text{Approximate } E_{old}(log(p(\mathbf{\Theta}, \mathbf{\Delta}|\mathbf{Y})))$$

$$\text{by } log(p(\mathbf{\Theta}_{old}, \hat{\mathbf{\Delta}}|\mathbf{Y}))$$

$$\hat{\mathbf{\Delta}} = argmax_{\mathbf{\Delta}} log(p(\mathbf{\Theta}_{old}, \mathbf{\Delta}|\mathbf{Y})$$

Model Fitting

- Challenging, multi-modal posterior
- Monte-Carlo EM (MCEM)
  - E-step: Sample factors through Gibbs sampling
  - M-step: Estimate regressions through off-the-shelf linear regression routines using sampled factors as response
    - We used t-regression, others like LASSO could be used
- Iterated Conditional Mode (ICM)
  - Replace E-step by CG : conditional modes of factors
  - M-step: Estimate regressions using the modes as response
- Incorporating uncertainty in factor estimates in MCEM helps

Latent dimension r	2	5	10	15
ICM	.9736	.9729	.9799	.9802
MCEM	.9728	.9722	.9714	.9715

Monte Carlo E-step

- Through a vanilla Gibbs sampler (conditionals closed form)

$$\text{Let } o_{ij} = y_{ij} - \alpha_i - \beta_j - x'_{ij}\boldsymbol{b}$$
$$Var[u_i|\text{Rest}] = (A_u^{-1} + \textstyle\sum_{j \in \mathcal{J}_i} \frac{v_j v'_j}{\sigma^2_{ij}})^{-1}$$
$$E[u_i|\text{Rest}] = Var[u_i|\text{Rest}](A_u^{-1} G w_i + \textstyle\sum_{j \in \mathcal{J}_i} \frac{o_{ij} v_j}{\sigma^2_{ij}})$$

- Other conditionals also Gaussian and closed form
- Conditionals of users (movies) sampled simultaneously
- Small number of samples in early iterations, large numbers in later iterations

M-step (Why MCEM is better than ICM)

- Update G, optimize

$$(E^*(u_{il}) - Gw_i)'(E^*(u_{il}) - Gw_i)$$

- Update $A_u = a_u I$

$$\hat{a_u} = \frac{\sum_{i=1}^{M}(E^*(u_i) - \hat{G}w_i)'(E^*(u_i) - \hat{G}w_i) + \sum_{k=1}^{r} Var^*(u_{ikl})}{Mr}$$

Ignored by ICM, underestimates factor variability
Factors over-shrunk, posterior not explored well

Experiment 1: Better regularization

- MovieLens-100K, avg RMSE using pre-specified splits
- ZeroMean, RLFM and FeatureOnly (no cold-start issues)
- Covariates:
  - Users : age, gender, zipcode (1st digit only)
  - Movies: genres

	RLFM	*ZeroMean*	*FeatureOnly*
MovieLens-100K	0.8956	0.9064	1.0968

Experiment 2: Better handling of Cold-start

- MovieLens-1M; EachMovie
- Training-test split based on timestamp
- Same covariates as in Experiment 1.

	MovieLens-1M			EachMovie		
Model	30%	60%	75%	30%	60%	75%
RLFM	0.9742	0.9528	0.9363	1.281	1.214	1.193
ZeroMean	0.9862	0.9614	0.9422	1.260	1.217	1.197
FeatureOnly	1.0923	1.0914	1.0906	1.277	1.272	1.266
FilterBot	0.9821	0.9648	0.9517	1.300	1.225	1.199
MostPopular	0.9831	0.9744	0.9726	1.300	1.227	1.205
Constant Model	1.118	1.123	1.119	1.306	1.302	1.298

Experiment 4: Predicting click-rate on articles

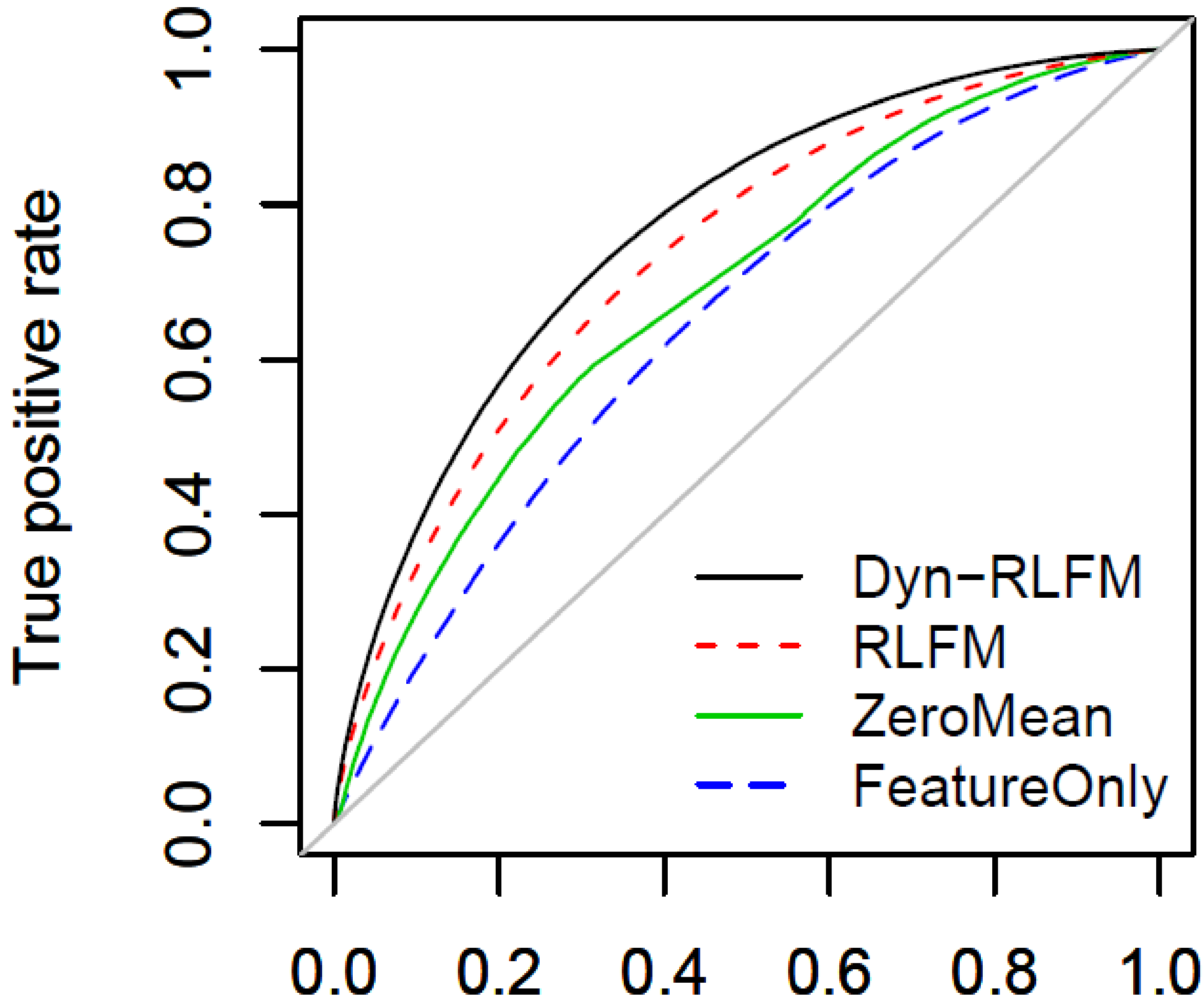
- Goal: Predict click-rate on articles for a user on F1 position
- Article lifetimes short, dynamic updates important

- User covariates:
  - Age, Gender, Geo, Browse behavior

- Article covariates
  - Content Category, keywords

- 2M ratings, 30K users, 4.5 K articles

Results on Y! FP data



Another Interesting Regularization on the factors

To incorporate neighborhood information like social network, hierarchies etc to regularize the factor estimates

$$u_i | u_{-i} \sim MVN\left(\sum_{j : j \in \mathcal{N}_i} \rho w_{ij} u_j / w_{i+}, \tau^2 / w_{i+} \right)$$

$$(u_1, \cdots, u_N) \sim MVN(\mathbf{0}, (D - \rho W) \otimes I)$$

Add Topic Discovery into Matrix Factorization

fLDA: Matrix Factorization through Latent Dirichlet Allocation

fLDA: Introduction

- Model the rating y_{ij} that user *i* gives to item *j* as the user's affinity to the topics that the item has

User *i* 's affinity to topic *k*

$$y_{ij} = \ldots + \sum_k s_{ik} \bar{z}_{jk}$$

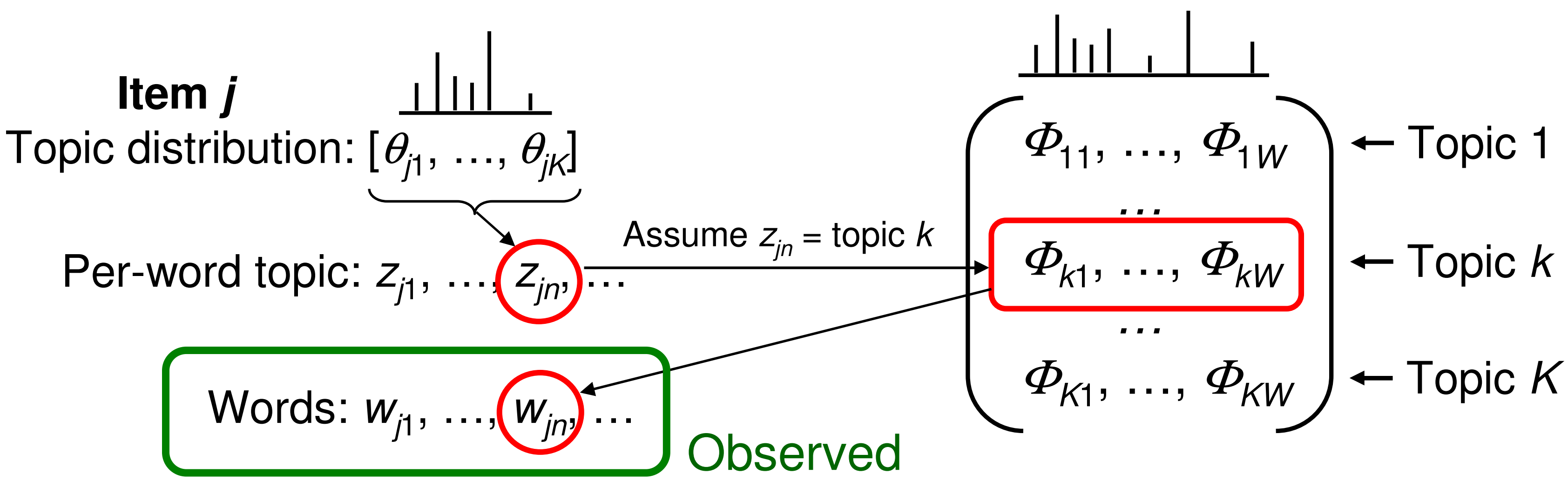
Pr(item *j* has topic *k*) estimated by averaging the LDA topic of each word in item *j*

Old items: z_{jk}'s are Item latent factors learnt from data with the LDA prior
New items: z_{jk}'s are predicted based on the bag of words in the items

– Unlike regular unsupervised LDA topic modeling, here the LDA topics are learnt in a supervised manner based on past rating data
– fLDA can be thought of as a "multi-task learning" version of the supervised LDA model [Blei'07] for cold-start recommendation

LDA Topic Modeling (1)

- LDA is effective for unsupervised topic discovery [Blei'03]
  - It models the generating process of a corpus of items (articles)
  - For each topic k, draw a word distribution $\Phi_k = [\Phi_{k1}, \ldots, \Phi_{kW}] \sim \text{Dir}(\eta)$
  - For each item j, draw a topic distribution $\theta_j = [\theta_{j1}, \ldots, \theta_{jK}] \sim \text{Dir}(\lambda)$
  - For each word, say the nth word, in item j,
    - Draw a topic z_{jn} for that word from $\theta_j = [\theta_{j1}, \ldots, \theta_{jK}]$
    - Draw a word w_{jn} from $\Phi_k = [\Phi_{k1}, \ldots, \Phi_{kW}]$ with topic $k = z_{jn}$



LDA Topic Modeling (2)

- Model training:
  - Estimate the prior parameters and the posterior topic×word distribution Φ based on a training corpus of items
  - EM + Gibbs sampling is a popular method
- Inference for new items
  - Compute the item topic distribution based on the prior parameters and Φ estimated in the training phase
- Supervised LDA [Blei'07]
  - Predict a target value for each item based on supervised LDA topics

Regression weight for topic *k* One regression per user

$$y_j = \sum_k s_k \bar{z}_{jk} \quad \text{vs.} \quad y_{ij} = \ldots + \sum_k s_{ik} \bar{z}_{jk}$$

Target value of item *j*

Same set of topics across different regressions

Pr(item *j* has topic *k*) estimated by averaging the topic of each word in item *j*

fLDA: Model

- **Rating:** $y_{ij} \sim N(\mu_{ij}, \sigma^2)$ Gaussian Model
  user *i* gives item *j* $y_{ij} \sim Bernoulli(\mu_{ij})$ Logistic Model (for binary rating)
  $y_{ij} \sim Poisson(\mu_{ij} N_{ij})$ Poisson Model (for counts)

$$t(\mu_{ij}) = x_{ij}^t b + \alpha_i + \beta_j + \textstyle\sum_k s_{ik} \bar{z}_{jk}$$

- **Bias of user *i*:** $\alpha_i = g_0^t x_i + \varepsilon_i^\alpha, \quad \varepsilon_i^\alpha \sim N(0, \sigma_\alpha^2)$
- **Popularity of item *j*:** $\beta_j = d_0^t x_j + \varepsilon_j^\beta, \quad \varepsilon_j^\beta \sim N(0, \sigma_\beta^2)$
- **Topic affinity of user *i*:** $s_i = H x_i + \varepsilon_i^s, \quad \varepsilon_i^s \sim N(0, \sigma_s^2 I)$
- **Pr(item *j* has topic *k*):** $\bar{z}_{jk} = \sum_n 1(z_{jn} = k) / (\#\text{words in item } j)$
  (z_{jn}: The LDA topic of the *n*th word in item *j*)
- **Observed words:** $w_{jn} \sim LDA(\lambda, \eta, z_{jn})$
  (w_{jn}: The *n*th word in item *j*)

Model Fitting

- Given:
  - Features $X = \{x_i, x_j, x_{ij}\}$
  - Observed ratings $y = \{y_{ij}\}$ and words $w = \{w_{jn}\}$
- Estimate:
  - Parameters: $\Theta = [b, g_0, d_0, H, \sigma^2, a_\alpha, a_\beta, A_s, \lambda, \eta]$
    - Regression weights and prior parameters
  - Latent factors: $\Delta = \{\alpha_i, \beta_j, s_i\}$ and $z = \{z_{jn}\}$
    - User factors, item factors and per-word topic assignment
- Empirical Bayes approach:
  - Maximum likelihood estimate of the parameters:

$$\hat{\Theta} = \arg\max_{\Theta} \Pr[y, w \mid \Theta] = \arg\max_{\Theta} \int \Pr[y, w, \Delta, z \mid \Theta] \, d\Delta dz$$

  - The posterior distribution of the factors:

$$\Pr[\Delta, z \mid y, \hat{\Theta}]$$

The EM Algorithm

- Iterate through the E and M steps until convergence
  - Let $\hat{\Theta}^{(n)}$ be the current estimate
  - E-step: Compute $$f(\Theta) = E_{(\Delta, z \mid y, w, \hat{\Theta}^{n})}[\log \Pr(y, w, \Delta, z \mid \Theta)]$$
    - The expectation is not in closed form
    - We draw Gibbs samples and compute the Monte Carlo mean
  - M-step: Find $$\hat{\Theta}^{(n+1)} = \arg\max_{\Theta} f(\Theta)$$
    - It consists of solving a number of regression and optimization problems

Supervised Topic Assignment

The topic of the *n*th word in item *j*

$$\Pr(z_{jn} = k \mid \text{Rest})$$

Probability of observing y_{ij} given the model

$$\propto \underbrace{\frac{Z_{kl}^{\neg jn} + \eta}{Z_{k}^{\neg jn} + W\eta}\left(Z_{jk}^{\neg jn} + \lambda\right)}_{\text{Same as unsupervised LDA}} \cdot \underbrace{\prod_{i \text{ rated } j} \overbrace{f(y_{ij} \mid z_{jn} = k)}}$$

Same as unsupervised LDA

Likelihood of observed ratings by users who rated item *j* when z_{jn} is set to topic *k*

fLDA: Experimental Results (Movie)

- Task: Predict the rating that a user would give a movie
- Training/test split:
  - Sort observations by time
  - First 75% → Training data
  - Last 25% → Test data
- Item warm-start scenario
  - Only 2% new items in test data

Model	Test RMSE
RLFM	0.9363
fLDA	0.9381
Factor-Only	0.9422
FilterBot	0.9517
unsup-LDA	0.9520
MostPopular	0.9726
Feature-Only	1.0906
Constant	1.1190

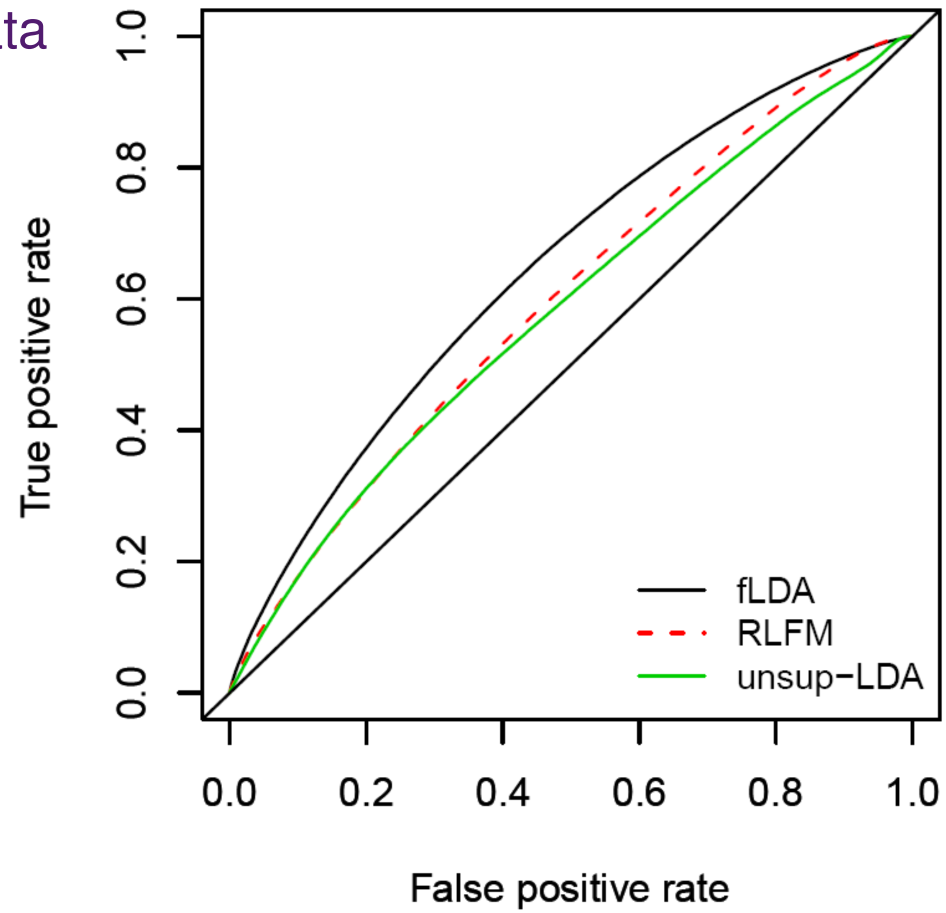
fLDA is as strong as the best method
It does not reduce the performance in warm-start scenarios

fLDA: Experimental Results (Yahoo! Buzz)

- Task: Predict whether a user would buzz-up an article
- Severe item cold-start
  - All items are new in test data

fLDA significantly outperforms other models

Data Statistics
1.2M observations
4K users
10K articles



Experimental Results: Buzzing Topics

3/4 topics are interpretable; 1/2 are similar to unsupervised topics

Top Terms (after stemming)	Topic
bush, tortur, interrog, terror, administr, CIA, offici, suspect, releas, investig, georg, memo, al	CIA interrogation
mexico, flu, pirat, swine, drug, ship, somali, border, mexican, hostag, offici, somalia, captain	Swine flu
NFL, player, team, suleman, game, nadya, star, high, octuplet, nadya_suleman, michael, week	NFL games
court, gai, marriag, suprem, right, judg, rule, sex, pope, supreme_court, appeal, ban, legal, allow	Gay marriage
palin, republican, parti, obama, limbaugh, sarah, rush, gop, presid, sarah_palin, sai, gov, alaska	Sarah Palin
idol, american, night, star, look, michel, win, dress, susan, danc, judg, boyl, michelle_obama	American idol
economi, recess, job, percent, econom, bank, expect, rate, jobless, year, unemploy, month	Recession
north, korea, china, north_korea, launch, nuclear, rocket, missil, south, said, russia	North Korea issues

fLDA Summary

- fLDA is a useful model for cold-start item recommendation
- It also provides interpretable recommendations for users
  - User's preference to interpretable LDA topics
- Future directions:
  - Investigate Gibbs sampling chains and the convergence properties of the EM algorithm
  - Apply fLDA to other multi-task prediction problems
    - fLDA can be used as a tool to generate supervised features (topics) from text data

Summary

- Regularizing factors through covariates effective
- We presented a regression based factor model that regularizes better and deals with both cold-start and warm-start in a single framework in a seamless way
- Fitting method scalable; Gibbs sampling for users and movies can be done in parallel. Regressions in M-step can be done with any off-the-shelf scalable linear regression routine